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iCDEEr™ (Integrated Core–Micro-Core, Digital Capability, Entrepreneurship, Ethics and Reform Curriculum): An AI-Enabled Higher Education Ecosystem for Curriculum, Competency, Learning, and Academic Intelligence

HM. Hamdani¹, Subhan Muhith², M Iman Tarmizi Thaher³, Rahma Zakiah Al Hamdnai⁴, Melawati⁵

¹Universitas Kader Bangsa, Indonesia

²Universitas Muhammadiyah Ahmad Dahlan Palembang, Indonesia

³Universitas Sriwijaya, Palembang, South Sumatra, Indonesia

⁴Universitas Muhammadiyah Palembang, Indonesia

⁵Universitas Aisyah Pringsewu, Indonesia

kangdani135@gmail.com

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Correspondence Address:

kangdani135@gmail.com

Abstract:

Higher education requires increasingly integrated use of educational evidence for curriculum improvement, competency development, learning and assessment, student support, and academic quality. The iCDEEr™ framework proposes a human-governed AI-enabled higher education ecosystem that connects these functions through a curriculum-and-competency core, learning and assessment evidence, institutional intelligence, AI-supported recommendations, human academic decision-making, implementation, outcomes, and continuous quality improvement. This article develops the framework as a conceptual research architecture rather than an empirical effectiveness model. Using structured conceptual synthesis of the iCDEEr™ Collaborative Research Master Framework and selected literature on AI in education, learning analytics, educational data, and responsible AI, the article identifies eight provisional intelligence domains: curriculum, competency, research, quality, career, academic scheduling, student support, and governance intelligence. The education-focused interpretation places curriculum, competency, learning, assessment, student support, and quality improvement at the centre while retaining the wider institutional domains as supporting functions. The article also specifies a Core–Micro-Core architecture, a human-governed AI decision cycle, potential educational outcomes, and a staged validation pathway from expert review and instrument development to pilot, multi-university, implementation, and longitudinal studies. The framework does not claim causal effects or empirical effectiveness. Its contribution is a structured research

language for investigating how educational evidence and AI-supported intelligence can inform higher education decisions while preserving human authority, transparency, privacy, and contextual interpretation.

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Introduction (مقدمة)

Higher education is increasingly expected to use educational evidence to improve curriculum relevance, competency development, learning, assessment, student support, and academic quality. Yet these evidence streams are often managed separately. Curriculum documents, competency frameworks, assessment records, student progress data, research outputs, quality-assurance evidence, career information, and operational records may exist in different systems and are not always connected for educational decision-making. Learning analytics research has emphasized the importance of linking data to learning processes rather than treating analytics as a purely technical activity (Gašević et al., 2015; Ifenthaler & Yau, 2020).

At the same time, artificial intelligence (AI) is becoming increasingly relevant to higher education through learning analytics, educational data mining, academic support, institutional analytics, and decision support. Reviews of AI in higher education show that the field extends beyond automated teaching functions to broader institutional and educational applications (Zawacki-Richter et al., 2019; Bond et al., 2024). Guidance from UNESCO and the U.S. Department of Education also stresses human oversight, transparency, privacy, and educational purpose when AI is introduced into education (Miao et al., 2021; Miao & Holmes, 2023; U.S. Department of Education, 2023).

These developments create an educational architecture problem: useful intelligence may be produced within separate functions, while curriculum and learning decisions require evidence from several functions at once. For example, a competency gap may be identified through assessment evidence, interpreted through curriculum mapping, discussed in relation to student support, and considered within quality-improvement processes. A coherent education-focused framework therefore needs to explain how evidence moves from learning activities to intelligence and then to academically accountable decisions.

The iCDEEr™ framework addresses this problem by positioning curriculum and competency as the organising core of a university academic ecosystem. Learning and assessment provide a central evidence-generation layer, while research, quality, career, scheduling, student-support, and governance information provide complementary evidence. AI is positioned as an intelligence and recommendation layer rather than an

autonomous educational authority. Human academic actors remain responsible for validating, approving, modifying, or rejecting recommendations.

The research gap addressed in this article is therefore architectural and educational rather than technological. Existing studies provide substantial knowledge about AI in education, learning analytics, educational data mining, and academic governance, but these strands are often examined as separate applications or functions. iCDEEr™ provides a common architecture for studying their relationships around curriculum, competency, learning, assessment, and continuous educational improvement.

This article contributes by translating the iCDEEr™ collaborative research framework into an education-focused conceptual article. It (1) defines a university educational ecosystem centred on curriculum and competency; (2) connects learning, assessment, institutional evidence, and educational intelligence; (3) clarifies the role of AI within a human-governed decision cycle; and (4) proposes researchable domains and a staged validation pathway without presenting untested constructs as established empirical measures.



Method (منهج)

This article uses a conceptual framework development approach based on structured synthesis. The primary source is the iCDEEr™ Collaborative Research Master Framework, which defines a multi-institutional research programme for AI-enabled university academic ecosystems. Because the source explicitly identifies itself as a research-development framework rather than an empirical effectiveness report, the present article does not introduce fabricated participants, datasets, statistical tests, or causal findings.

The synthesis process consisted of four analytical steps. First, the source framework was decomposed into its principal educational and institutional elements: context and need, academic core, Micro-Core, learning and assessment, evidence generation, intelligence, human academic decision, implementation and outcomes, and continuous quality improvement. Second, relationships among these elements were reorganised around an education-focused logic in which curriculum and competency provide the organising core. Third, the eight intelligence domains retained from the source were interpreted in relation to educational decision-making. Fourth, the proposed validation phases were aligned with the methodological requirement that constructs, indicators, instruments, and causal relationships must undergo expert review, pilot testing, reliability and validity assessment, and empirical validation before stronger claims are made.

The unit of analysis is the conceptual relationship among components of a higher education ecosystem rather than an individual student, lecturer, programme, or institution. The framework is therefore treated as a research proposition that can be operationalised differently across educational contexts. The synthesis also draws on established literature on learning analytics, AI in education, educational data, and responsible AI to situate the framework within current higher education research.

1. Conceptual Architecture of the iCDEEr™ Higher Education Ecosystem

Layer	Core Elements	Researchable Evidence
Context / Need	Societal, professional, labour-market, scientific, and institutional needs	Needs assessment; policy documents; employer evidence; stakeholder surveys
Academic Core	Programme identity, disciplinary foundation, fundamental competencies	Curriculum mapping; learning outcomes; expert review
Micro-Core	Specialised and emerging competency pathways	Competency frameworks; pathway mapping; industry/scientific relevance
Learning & Assessment	Teaching, learning, assessment, and portfolios	Learning outcomes; assessment records; portfolios; student experience
Evidence Generation	Learning, assessment, research, tracer, employer, and quality evidence	Structured institutional datasets and evidence inventories
Intelligence Layer	Curriculum, competency, research, quality, career, scheduling, student-support, and governance intelligence	Analytics outputs; recommendations; dashboards; decision logs
Human Academic Decision	Validation, approval, modification, or rejection	Decision records; committee processes; expert review; governance audit
Implementation & Outcomes	Curriculum changes, support actions, research/career/quality activities	Implementation records; competency; employability; research; quality indicators
CQI	Continuous monitoring and curriculum/institutional improvement	Repeated measures; review cycles; improvement actions

نتائج (Result)

The conceptual synthesis produced an integrated higher education architecture in which curriculum and competency occupy the organising core, while learning and assessment provide the main educational evidence pathway. The wider ecosystem connects institutional needs, curriculum design, specialised competency pathways, learning activities, assessment, research, quality assurance, career information, student support, academic scheduling, and governance. Evidence generated from these activities is transformed into intelligence and recommendations, after which human academic actors make context-sensitive decisions. The cycle can be expressed as: Need → Core → Micro-Core → Competency → Learning & Assessment → Evidence → Intelligence → AI-Supported Recommendation → Human Academic Decision → Implementation → Outcomes → Continuous Quality Improvement.

Eight provisional intelligence domains were retained from the source framework. For an education-focused interpretation, Curriculum Intelligence and Competency Intelligence form the most direct link to educational design and learning outcomes; Student Support Intelligence connects evidence to learner support; Quality Intelligence connects evidence to continuous improvement; Academic Scheduling Intelligence addresses educational operations; Research and Career Intelligence provide complementary academic and graduate-development evidence; and Governance Intelligence establishes the conditions for responsible use of AI and institutional data. These domains are research-development constructs and should not be interpreted as validated scales until empirical testing is completed.

Construct	Provisional Definition	Potential Evidence / Indicators
Curriculum Intelligence	Capacity to use evidence to identify curriculum gaps and support curriculum improvement.	Curriculum evaluation; competency gaps; employer feedback; scientific developments; review actions
Competency Intelligence	Capacity to profile competency attainment and identify skill gaps.	Assessment; learning outcomes; portfolios; Core-Micro-Core evidence; attainment
Research Intelligence	Capacity to support research pathways, collaboration, productivity, and publication opportunities.	Projects; publications; books; citations; research interests; collaborations
Quality Intelligence	Capacity to identify quality gaps and support continuous quality improvement and accreditation readiness.	SPMI/quality evidence; self-evaluation; review findings; improvement actions

Construct	Provisional Definition	Potential Evidence / Indicators
Career Intelligence	Capacity to connect competencies with career and employability pathways.	Tracer studies; employer feedback; competencies; career pathways
Academic Scheduling Intelligence	Capacity to support scheduling and identify operational conflicts.	Calendar; workload; rooms; courses; lecturer availability; conflict records
Student Support Intelligence	Capacity to identify early-warning signals and recommend appropriate support.	Academic progress; attendance; assessment; engagement; support actions
Governance Intelligence	Capacity to support transparency, traceability, accountability, and responsible AI governance.	AI logs; recommendations; approvals; policies; audit trails; governance reviews

The synthesis also identifies eight broad outcome domains: curriculum responsiveness, competency attainment, student success, research productivity and impact, graduate employability, quality and accreditation readiness, academic operational efficiency, and responsible AI governance. In an education-focused research programme, curriculum responsiveness, competency attainment, student success, and quality improvement are particularly central because they connect the framework directly to educational processes and outcomes. The remaining domains provide supporting evidence for the wider university ecosystem.

Outcome Domain	Examples of Potential Measures
Curriculum responsiveness	Alignment with programme outcomes, professional needs, employer/scientific feedback, and documented curriculum improvements
Competency attainment	Achievement of defined learning/graduate competencies, competency gaps, and progression
Student success	Retention, progression, completion, engagement, and support response
Research productivity and impact	Research outputs, collaborations, publications, citations, and dissemination

Outcome Domain	Examples of Potential Measures
Graduate employability	Employment status, relevance of employment, employer feedback, and competency-career alignment
Quality and accreditation readiness	CQI actions, evidence completeness, internal review findings, and accreditation preparation
Academic operational efficiency	Scheduling conflicts, workload balance, resource utilisation, and delay indicators
Responsible AI governance	Human approval rates, explainability evidence, auditability, transparency, trust, and governance compliance



Discussion (مناقشة)

1. From Fragmented Educational Evidence to an Integrated Ecosystem

The central educational significance of iCDEEr™ is its shift from isolated AI applications toward an integrated evidence architecture. Learning analytics has demonstrated the value of using educational data to understand learning processes and support study success (Long & Siemens, 2011; Ifenthaler & Yau, 2020). However, educational decisions such as curriculum revision or competency improvement often require evidence beyond a single learning platform. iCDEEr™ therefore treats the educational ecosystem as the unit of analysis while keeping curriculum and competency at its centre.

This integration matters because educational decisions are interdependent. A curriculum gap may become visible through assessment results; the same gap may be interpreted through competency mapping, student feedback, employer evidence, or scientific developments; and an improvement action may subsequently be evaluated through quality-assurance evidence. The framework provides a conceptual pathway for connecting these evidence sources rather than assuming that one dashboard or one AI model can represent the whole educational process.

2. Core-Micro-Core as an Organising Curriculum Architecture

The Core-Micro-Core structure positions programme identity and disciplinary foundations alongside specialised or emerging competency pathways. In educational terms, the Core represents the stable knowledge, values, and foundational competencies expected within a programme, while the Micro-Core accommodates specialised, contextual, or emerging competencies. This structure allows curriculum development to respond to changing professional and scientific needs without abandoning programme identity.

The architecture also creates a direct link between curriculum intelligence and competency intelligence. Curriculum intelligence can identify alignment or gaps between

programme learning outcomes, course content, and external needs, while competency intelligence can examine whether learners demonstrate the intended outcomes. Together, these functions support evidence-informed curriculum improvement and assessment design. The framework therefore places educational evidence, rather than AI technology itself, at the centre of curriculum decision-making.

3. AI as an Intelligence Layer in Educational Decision-Making

A defining characteristic of the framework is the placement of AI between evidence generation and human academic decision-making. AI is expected to analyse evidence, identify patterns, and generate recommendations; it does not receive autonomous authority to determine curriculum changes, student interventions, assessment decisions, or institutional policies. This distinction is consistent with broader discussions of human-centred AI in education and the need to preserve educational judgement (Selwyn, 2019; Miao & Holmes, 2023).

This human-governed structure is particularly relevant to learning analytics and generative AI. Educational data can contain incomplete, contextual, or sensitive information, and algorithmic outputs may be difficult to interpret without disciplinary and pedagogical knowledge. Responsible educational AI therefore requires transparency about data sources, limitations, intended use, and decision authority. Governance Intelligence in the iCDEEr™ framework provides a conceptual mechanism for documenting these responsibilities.

The proposed decision cycle can consequently be understood as Evidence → Intelligence → Recommendation → Human Review → Educational Decision → Implementation → Outcome Evidence. This sequence makes accountability visible and creates a basis for auditing whether AI-supported recommendations were accepted, modified, or rejected. It also recognises that educational quality depends on contextual interpretation rather than prediction alone.

4. Eight Intelligence Domains as an Education Research Programme

The eight intelligence domains allow the broad ecosystem concept to be decomposed into researchable modules. For education research, the most immediate modules are curriculum, competency, student support, and quality intelligence because they directly concern learning and educational improvement. Research, career, scheduling, and governance intelligence extend the framework to other functions that shape the educational environment. The modular structure means that researchers can validate individual domains before examining the full ecosystem.

The modular structure has methodological advantages. A university does not need to implement the complete ecosystem before generating evidence about one educational function. Researchers may first validate curriculum or competency indicators, examine student-support use cases, or test the feasibility of a governance protocol. Findings from these modules can later be integrated into multi-domain studies. This approach is consistent with the source framework's staged research programme and reduces the risk of treating a complex conceptual model as a single untestable intervention.

5. Responsible Educational Data Use, Privacy, and Context

An integrated educational intelligence architecture necessarily increases the importance of data governance. Student records, assessment results, learning behaviour, support histories, and career information may contain sensitive information. The source framework therefore requires local ethical approval where applicable, data protection, de-identification, minimisation of sensitive data, fairness, transparency, explainability, and human oversight. These requirements are consistent with established ethical discussions in learning analytics (Pardo & Siemens, 2014; Slade & Prinsloo, 2013; West et al., 2016).

The framework also adopts a federated collaboration model so that participating institutions can contribute to a common educational research programme while retaining responsibility for local data and governance. Common constructs, data definitions, and methodological procedures can support comparison across institutions, but contextual differences should remain visible. The purpose is not to impose one universal educational model, but to create a shared language for examining how evidence and intelligence support educational improvement.

6. From Conceptual Architecture to Empirical Educational Validation

The most important methodological implication is that iCDEEr™ should be validated progressively. The source framework proposes conceptual refinement, expert validation, instrument development, pilot testing, multi-university research, implementation studies, and longitudinal evaluation. For an education-focused programme, this sequence allows researchers to test whether proposed curriculum, competency, learning, student-support, and governance indicators are clear, relevant, feasible, reliable, and valid before they are used for broader comparisons.

Phase	Primary Purpose	Expected Evidence
1. Conceptual refinement	Refine constructs, definitions, relationships, and boundary conditions.	Expert discussion; revised construct map
2. Expert validation	Assess relevance, clarity, completeness, and contextual applicability.	Content-validity evidence; expert consensus
3. Instrument development	Develop items, evidence templates, data dictionary, and scoring procedures.	Reliability and validity evidence
4. Pilot study	Test feasibility, data availability, respondent burden, and analysis procedures.	Pilot dataset; feasibility findings
5. Multi-university study	Compare patterns across programmes, disciplines, institutions, and countries.	Harmonised multi-site evidence

Phase	Primary Purpose	Expected Evidence
6. Implementation study	Evaluate usability, governance, implementation processes, and selected outcomes.	Implementation and outcome evidence
7. Longitudinal evaluation	Examine change, sustainability, and temporal relationships.	Repeated measures; longitudinal evidence

This staged pathway defines what evidence is required before stronger claims can be made. Expert review can establish content relevance and clarity; instrument studies can examine reliability and validity; pilot studies can establish feasibility; multi-university studies can examine contextual variation; implementation studies can examine usability and governance; and longitudinal research can examine change over time. The framework therefore supports an empirical research agenda while maintaining a clear boundary between conceptual propositions and demonstrated educational effects.

7. Implications for Higher Education Research and Educational Practice

For educational researchers, iCDEEr™ provides a common architecture for designing studies that connect curriculum, competency, learning, assessment, student support, quality, and institutional evidence. For higher education institutions, it provides a way to discuss AI not simply as a classroom technology but as part of an evidence-informed educational ecosystem. For curriculum leaders and academic quality teams, the Core-Micro-Core structure offers a conceptual bridge between programme identity, emerging competencies, assessment evidence, and continuous improvement.

The framework should nevertheless be treated as a research proposition, not a universal institutional prescription. Different disciplines, programmes, countries, and institutional missions may require different evidence sources, indicators, and governance arrangements. Its value must therefore be established through empirical validation and contextual interpretation. This limitation is essential because AI-supported educational decision-making can create risks if data availability is mistaken for educational validity or if algorithmic recommendations are treated as authoritative without human review.



Conclusion (خاتمة)

The iCDEEr™ framework proposes a human-governed AI-enabled higher education ecosystem in which curriculum and competency function as the organising educational core, learning and assessment generate central evidence, and institutional intelligence connects evidence to academic decision-making. The framework integrates eight provisional intelligence domains—curriculum, competency, research, quality, career, academic scheduling, student support, and governance—within a cycle of evidence, intelligence, AI-supported recommendation, human academic decision, implementation, and continuous quality improvement.

As a conceptual article, this study does not establish empirical effectiveness, causal relationships, or universal applicability. Its contribution is a structured research architecture for investigating how educational evidence can be integrated responsibly across higher education functions. Future research should prioritise expert validation, instrument development, pilot testing, multi-institutional comparison, implementation studies, and longitudinal evaluation, with particular attention to curriculum relevance, competency attainment, student success, educational quality, privacy, transparency, and human governance.

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